IN THE CLAIMS:

The following listing of claims will replace all prior versions, and listings, of claims in the application.

1. (Currently Amended) A process controller comprising:

controller variable inputs comprised of measurements of process variable inputs of the process being controlled, wherein the process variable inputs include at least one manipulated variable, and wherein said at least one manipulated variable comprises a magnetic field strength, shape, location and/or orientation within a particle accelerator;

a dynamic predictive model[[,]] of the process being controlled, with one or more dynamic predictive model parameters[[(s),]] for receiving current variable input values, wherein the one or more dynamic predictive model parameters[[(s)]] change[[(s)]] dependent on said variable input values received by the controller; and

one or more outputs[[(s)]] from the dynamic model for generating controller outputs for effectuating change to variable outputs of the process being controlled, wherein said variable outputs comprise particle positions within the particle accelerator.

2. (Currently Amended) The controller of claim 1 wherein the dynamic predictive model is further comprised of:

a physical model with physical model parameters that vary with said variable inputs; and

an empirical model which adjusts the physical model's parameters based on the controller variable inputs.

3. (Currently Amended) The controller of claim 2 wherein the empirical model's adjustments to the physical model's parameters based on the controller variable inputs [[is]] are further based on historical controller inputs.

4. (Original) The controller of claim 2 where the physical model is a first principles model of the process being controlled.

5. (Currently Amended) The controller of claim 2 where the empirical model[[s]] is a non-linear model.

6. (Original) The controller of claim 2 where the non-linear model is a neural network.

7. (Original) The controller of claim 2 wherein the physical model is a first principles model of the process being controlled and the empirical model is a non-linear neural network that adjusts the parameters of the first principle model based on the controller variable inputs.

8. (Original) The controller of claim 7 wherein the physical model is a first principles model of the process being controlled and the empirical model is a non-linear neural network that adjusts the parameters of the first principle model based on the current controller variable inputs.

9. (Original) The controller of claim 7 wherein the physical model is a first principles model of the process being controlled and the empirical model is a non-linear neural network that adjusts the parameters of the first principle model based on the current and historical controller variable inputs.

10. (Currently Amended) A process control system comprising:

a distributed control system that [[further]] comprises:

a computing device operable to execute a first software tool that identifies variable inputs including at least one manipulated variable input, and controlled variables associated with the process, wherein said first software tool is further operable to determine relationships between said variable input[[(s)]]s and said controlled variables; and

at least one controller operable to monitor said variable inputs ~~parameter(s)~~ and tune said at least one manipulated variable[[s]] input;

wherein said at least one manipulated variable input comprises a strength, shape, location and/or orientation of a magnetic field in a particle accelerator, and said controlled variables comprise particle positions within the particle accelerator.

11. (Currently Amended) The process control system of claim 10, wherein said relationships between said variable input[[(s)]]s and said controlled variables comprises [[a]] one or more first principle model[[(s)]]s with model parameters wherein values of said [[first principle]] model parameter [[values]] are dependent on said variable input[[(s)]]s.

12. (Original) The process control system of claim 10, further comprising neural networks utilized to identify said model parameters.

13. (Currently Amended) The process control system of [[C]]claim 10, wherein the software tool utilizes a neural network to determine said ~~step of determining~~ relationships between said variable inputs[[(s)]] and said controlled variables ~~utilizes a neural network~~.

14. (Currently Amended) The process control system of claim 10, wherein the software tool utilizes a combination of physical models and empirical methods to determine said ~~step of determining the~~ relationship between said variable inputs and said controlled variables ~~utilizes a combination of physical models and empirical methods~~.

15. (Original) The process control system of claim 13 wherein said physical models and empirical methods are combined in parallel and/or in series.

16. (Original) The process control system of claim 13 wherein said physical model parameters[[(s)]] vary[[ies]] over an operating range.

17. (Original) The process control system of claim 14 wherein said physical model is a function of said variable inputs[[(s)]].

18. (Currently Amended) The process control system of claim 16 wherein said physical model comprises first principle parameters which vary with said variable inputs[[(s)]], wherein said empirical methods comprise a neural network used to identify first principle parameter values associated with said variable inputs[[(s)]] and wherein said neural network updates said first principle parameters with values associated with said variable inputs[[(s)]].

19. (Original) The process control system of claim 18 wherein said neural network is trained.

20. (Original) The process control system of claim 18 wherein said neural network is trained according to at least one method selected from the group consisting of: gradient methods, back propagation, gradient-based nonlinear programming methods, sequential quadratic programming, generalized reduced gradient methods, and non-gradient methods.

21. (Original) The process control system of claim 20 wherein gradient methods require gradients of an error with respect to a weight and bias obtained by numerical derivatives.

22. (Original) The process control system of claim 20 wherein gradient methods require gradients of an error with respect to a weight and bias obtained by analytical derivatives.

23. (Cancelled).

24. (Currently Amended) The process control system of claim [[23]]10, wherein a step of tuning the [[control]] at least one manipulated variable comprises adjusting a [[connector]] corrector magnet and/or quadr[[a]]upole magnet.

25. (Currently Amended) A dynamic process controller ~~predicting a change in the dynamic variable input values to the process to effect a change in the controlled variable output of the process from a current controlled variable output value at a first time to a different and desired controlled variable output value at a second time,~~ comprising:

a dynamic predictive model for receiving ~~the current~~ variable input values of a process, wherein the variable input values include at least one manipulated variable value, and wherein said at least one manipulated variable value comprises a magnetic field strength, shape, location and/or orientation value within a particle accelerator, wherein said dynamic predictive model changes dependent upon said variable input values[[,]] and [[the]] [[desired]] controlled variable output values of the process, wherein said controlled variable output values comprise particle positions within the particle accelerator, and wherein said dynamic predictive model is used to produce[[s]] a plurality of desired [[controlled]] manipulated variable input values at different time positions between [[the]] a first time and [[the]] a second time to define a dynamic operation path of the process between ~~the current~~ controlled variable output values of the process at the first time and [[the]] desired controlled variable output values of the process at the second time; and

an optimizer for optimizing ~~the operation of the dynamic controller over a plurality of the different time positions~~ the plurality of desired manipulated variable input values in accordance with a predetermined optimization method that optimizes the ~~objectives of the dynamic controller to achieve a desired~~ dynamic operation path in accordance with the changing dynamic predictive model~~, such that the objectives of the dynamic predictive model vary as a function of time~~.

26. (Currently Amended) The dynamic process controller of claim 25, wherein said dynamic predictive model comprises:

a dynamic forward model operable to receive variable input values of the process

at each of said time positions and map said variable input values to [[components]] parameters of said dynamic predictive model associated with said received variable input values in order to provide [[a]] predicted dynamic controlled variable output values;

an error generator for comparing the predicted dynamic controlled variable output values to the desired controlled variable output values, and generating [[a]] primary error values as the differences for each of said time positions;

an error minimization device for determining [[a]] changes in the variable input values to minimize the primary error values output by said error generator;

a summation device for summing said determined changes in the variable input [[change]] values with ~~an original~~ the variable input values, which [[original]] variable input values comprise[[s]] the variable input values before the determined changes therein, for [[a]] the plurality of time positions to generate variable input values for the plurality of time positions~~to provide a future variable input value as a summed input value~~; and

a controller for controlling the operation of said error minimization device to operate under control of said optimizer to minimize said primary error values in accordance with said optimization method.

27. (Currently Amended) A method for controlling operating process, comprising the steps of:

identifying one or more variable input[[(s)]]s comprising a strength, shape, location and/or orientation of a magnetic field in a particle accelerator, and one or more controlled variables comprising particle positions within the particle accelerator ~~associated with the process~~, wherein at least one of said variable inputs is a manipulated variable;

determining relationships between said one or more variable input[[(s)]]s and said one or more controlled variables, wherein said relationship comprises models, and wherein parameters within said models are dependent on value said one or more variable inputs; and

tuning said at least one manipulated variable to achieve a desired controlled

variable value.

28. (Currently Amended) The method of [[C]]claim 27, further including the step of determining the relationship between the variable inputs and the model parameters wherein said relationship comprises a model.

29. (Currently Amended) The method of [[C]]claim 27, wherein said step of identifying relationships between variable inputs and control variables utilizes neural networks.

30. (Currently Amended) The method of [[C]]claim 28, wherein said step of identifying relationship between the variable input(s) and dynamic model parameters utilizes neural networks.

31. (Currently Amended) The method of [[C]]claim 27, wherein said step of determining relationships between said variable input(s) and said controlled variable(s) utilizes a combination of physical models and empirical methods.

32. (Currently Amended) The method of [[C]]claim 31, wherein said physical models and empirical methods are combined in series.

33. (Currently Amended) The method of [[C]]claim 31, wherein said physical models and empirical methods are combined in parallel.

34. (Currently Amended) The method of [[C]]claim 31, wherein said physical model varies over an operating range.

35. (Currently Amended) The method of [[C]]claim 34, wherein said physical model is a function of said input parameters.

36. (Currently Amended) The method of [[. C]]claim 35, wherein said physical model comprises first principle parameters which vary with said variable inputs, wherein empirical methods comprise a neural network used to identify first principle parameters values associated with said variable input(s), and wherein said neural network updates said first principle parameters with values associated with said variable input(s).

37. (Currently Amended) The method of [[C]]claim 36, wherein said neural network is trained.

38. (Currently Amended) The method of [[C]]claim 37, wherein said neural network is trained according to at least one method selected from the group consisting of gradient methods, back propagation, gradient-based nonlinear programming (NLP) methods, sequential quadratic programming, generalized reduced gradient methods, and non-gradient methods.

39. (Currently Amended) The method of [[C]]claim 38, wherein gradient methods require gradients of an error with respect to a weight and bias obtained by either numerical derivatives or analytical derivatives.